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14. ABSTRACT
Over the last five to seven years the use of chat in military contexts has expanded quite significantly, in some cases becoming a primary means of communicating time-sensitive data to decision makers and operators. The informal nature of chat communications allows the relay of far more information than the technical content of messages. Unlike formal documents such as newspapers, chat is often emotive. "Reading between the lines" to understand the connotative meaning of communication exchanges is now feasible, and is necessary to enable more useful automatic intelligence exploitation. The research project described in this paper was directed at recognizing user connotations of uncertainty and urgency. The project built a matrix of speech features indicative of these categories of meaning, developed data mining software to recognize them, and evaluated the results.

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Recognizing Connotative Meaning in Military Chat Communications

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ABSTRACT

Over the last five to seven years the use of chat in military contexts has expanded quite significantly, in some cases becoming a primary means of communicating time-sensitive data to decision makers and operators. For example, during humanitarian operations with Joint Task Force-Katrina, chat was used extensively to plan, task, and coordinate pre-deployment and ongoing operations. The informal nature of chat communications allows the relay of far more information than the technical content of messages. Unlike formal documents such as newspapers, chat is often emotive. "Reading between the lines" to understand the connotative meaning of communication exchanges is now feasible, and often important. Understanding the connotative meaning of text is necessary to enable more useful automatic intelligence exploitation. The research project described in this paper was directed at recognizing user connotations of uncertainty and urgency. The project built a matrix of speech features indicative of these categories of meaning, developed data mining software to recognize them, and evaluated the results.

Keywords: connotative meaning, chat communications, text processing, intelligence analysis

1. INTRODUCTION

Chat has become an important command and control medium, not to replace existing formal communications, but to enhance them by allowing timelier, more accurate, and more reliable planning, directing, and controlling of forces pursuant to the mission assigned[14]. Eovito's chat use assessment states that warfighters choose to use chat because it is fast, convenient, dependable, and efficient[2]. Chat messages can be quickly disseminated to everyone involved in preparing an operation, allowing them to begin their preparation without delay. Furthermore, collaboration among chat users does not require looking up electronic mail addresses, telephone numbers, or radio network identifications. Military chat users surveyed felt that without the use of chat, their situation awareness would be diminished, and information dissemination and coordination would be more difficult[13]. In 2003, the United States Navy conducted a survey of chat usage by those on deployment for Operation Iraqi Freedom; the majority of the one hundred eight three respondents indicated they used chat for over seven hours per day, six to seven days per week[1]. The increase in military chat use has made automatic processing of chat text necessary to provide for automated data collection, collation, and usage in new capabilities such as tactical updates, post-mission operational analysis, and watch turnover.

Unlike formal documents, such as newspapers, chat is often emotive, which allows the relay of far more information than just the technical content of messages. "Reading between the lines" to understand the connotative meaning of communication exchanges is now feasible and may become important for sounding alerts, for understanding behavior for after-action reviews, for participant identification verification, and for data collection and analysis.

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The remainder of this paper is organized as follows. Section 2 discusses the background for this research. Section 3 describes the techniques used to recognize connotations of uncertainty and urgency expressed in chat messages, and the results of these techniques are discussed in Section 4.

2. BACKGROUND

Most text analysis research to date has been on grammatical, well-formed text, such as articles from the Wall Street Journal. Analysis of chat text offers new challenges due to its dynamic nature. Chat messages often include misspellings, extra or missing capitalization, improper grammar constructs, non-standard punctuation, abbreviations, interwoven conversations, and other unique characteristics. Some of the processing methodologies for linguistic analysis of grammatical text are being expanded to account for the special characteristics of text chat data (three of many examples: [Srihari and Schwartzmyer; 2007], [Berube, et al; 2007] and [Carpenter; 2008]). A number of other research studies are attempting to detect less concrete aspects of chat communications. Some of them have focused on detecting general emotion cues ([Glazer; 2002], [Hancock, et al; 2007]). Other topics of chat study include the detection of empathy ([Pfeil and Zaphiris; 2007]), the detection of verbal irony ([Hancock, 2004]), and the detection of certainty (or confidence) and the measurement of the polarity of chat-detected sentiments, for example, negative/positive and favorable/unfavorable ([Liddy; 2004]).

3. APPROACH

The objectives of this research were to: (1) conduct a study of how humans recognize connotative cues expressing uncertainty and urgency, (2) formulate linguistic and non-linguistic means for recognizing those cues, (3) develop prototype algorithms to automatically perform recognition, and (4) evaluate the prototype recognition algorithms. A combination of off-the-shelf tools and novel approaches were utilized in algorithm development, and standard information extraction metrics were used for performance evaluation. Four hundred fifty-nine lines of chat data from military exercises were used for this research.

3.1 Rule-based analysis: identifying and detecting cues

A manual review of the data was performed to attempt to understand what cues were indicative of uncertainty and urgency. The data was reviewed for linguistic and non-linguistic cues. Linguistic cues were those such as the use of particular words and phrases. Non-linguistic cues under investigation included terse/lengthy responses (presuming that lengthy responses are very rarely used under circumstances of urgency or uncertainty), the use of capitalization, punctuation (including ellipsis), abbreviations, irregular spelling, and metadata values.

Often, one sign of emotion in general chat communications is the use of capitalized words as a means of indicating high emotions or angry screaming. We found that the use of capitalization in our military chat data is used for catching attention or alerting other chat participants to important information; it is rarely, if ever, used for "screaming."

Punctuation has been referred to as the 'prosody of online communication'[7], providing the equivalent of speech intonation in text to relay connotative meaning. In many ways chat communications are similar to transcribed spoken dialogue. For instance, they often contain interjections, such as "ah!" and "drat!" However, in a distinction from general chat, the military chat interjections we observed rarely included the identifying punctuation.

Abbreviations that are common in general chat communications, such as "msg" ("message") and "thx" ("thanks"), were present in our dataset along with an additional set of chat abbreviations that are specific to military communications (for instance, "w/u" to mean "wheels up"). [ALSA; 2009], a developing document to facilitate coordination of military chat use, recommends avoiding "civilian convenience" abbreviations and includes a table of standardized chat terminology. Some abbreviations are easily recognizable and commonly used in civilian chat, for example "arr" (arrived), "neg"

(negative), and “unk” (unknown); other abbreviations are unique to the military domain. The data used for this project was not limited by the restrictions suggested in [ALSA; 2009].

Irregular spelling could be accidental misspelling, potentially due to rushed typing, or a purposeful expression (ex. “riiiight” as an indication of the mental dawning of agreement, as opposed to “right” as an indication of simple, immediate agreement). As in transcribed speech, ellipsis, the trail of dots that indicates an incomplete thought or an omission of words (ex. “Well, if that’s so…”), is very common in both general and military chat communications.

Metadata values, such as the identification of the chat participant and the associated temporal label at the beginning of each message, are distinctive characteristics of chat communication that are not available in formal texts and can offer valuable information for processing systems. For example, for our purposes in this project, knowledge of the functional role and status of particular speakers could have been important input to the determination of connotative intent. However, that information was not available to us. The temporal component of the metadata was determined to be of no use in recognizing either urgency or uncertainty in this project. Exchanges were sometimes made across more than one room (question is made in one room, answer is given in another), communication seemed lax with lengthy response times (possibly due to the fact that it is data from an exercise), and dialogue sequences were difficult to untangle.

3.1.1 Cues for uncertainty and urgency

We found uncertainty and urgency cues to be quite subtle in the data. In our definition of uncertainty, we were looking for messages expressing more than a simple need for information. For example, the single message “What time are we striking?” with no other questions near it would be considered a simple request for information. However, when there are multiple questions in one message or across consecutive messages, the person(s) involved is (are) more likely to be demonstrating a state of confusion (that is, uncertainty). Urgency, from our manual review of the data, seemed to be fairly cut and dry, and dependent on keywords. Messages that ended with “ASAP”, “immediately”, or “press” were very likely to be expressing urgency. Messages ending with “now” were a little more difficult to categorize, as the message could be “Get this done now”, or it could be “I’m working this now”. The first may be expressing urgency; the second is more of a status update. Other than keywords, we did not recognize any syntax that seemed to express urgency. As noted earlier, capitalization did not provide significant evidence of urgency in our data, as it is used largely just to catch the attention of the intended recipients. The use of capitalized “NO” to indicate urgency was a rare exception. Exclamation points were rarely used, and usually did not convey urgency.

The cues we found for both uncertainty and urgency appeared to give varying levels of confidence, so confidence scores of 1 to 5 (5 indicating the highest confidence) were attached to each cue. Within a message, it is possible for multiple cues for one connotative meaning to be present; in these cases, the scores of each cue are added to determine the confidence level of the indicated connoted meaning. Table 1 lists the cues and scores that were developed through the manual review, an explanation for each cue, and the connoted meaning. Note that examples given are very simple and intended only for illustration of the syntax being described.

3.1.2 Rule-based analysis: detecting cues

It was determined that most of the cues recognized during the manual review could be captured by regular expressions (recognizable patterns that can be interpreted into software code). A prototype Java software program was developed to perform the recognition of rule-based cues. One of the cues (#7: “Which [noun]?”) would require recognition of the classification of a word as a ‘noun’ by a software parser and, although the rule is probably pertinent, it would not have been applied many times in relation to the time and effort it would have taken to implement it. Therefore, rule #7 was not implemented in the software.

Table 1: Cues developed by manual review of data

	Cue Description	Explanation	Connoted Meaning	Points (1 - 5)
1	Two or more questions in one message.	One speaker, one message, with two or more questions. More questions within one message indicate more uncertainty.	uncertainty	5
2	Questions with an option.	A question that gives a choice. Example: "Should target A be our priority, or is target B more important?"	uncertainty	4
3	One speaker with two or more questions in consecutive messages.	Example: Person A: "Are we striking at 1400?" Person B: "affirmative, strike at 1400." Person A: "copy, what are the coords for the strike?" Person B: "56N 138W"	uncertainty	4
4	Two or more consecutive questions across speakers.	In consecutive messages, regardless of speaker, each message has at least one question. Example: Person A: "Are we striking at 1400?" Person B: "Is the location still 56N 138W?"	uncertainty	4
5	Multiple question marks at the end of a question.	More question marks usually mean more uncertainty.	uncertainty	3
6	"understand" and a question mark in a message.	Example: "I don't understand. Weren't we targeting A?"	uncertainty	3
7	"Which [noun]?"	Self-explanatory.	uncertainty	3
8	Question and ellipsis in one message.	Examples: "What time are we striking? I lost the info…" "Do you know who we are looking for…?"	uncertainty	2
9	Ellipsis	Sentence within a message ends with "…"	uncertainty	1
10	"ASAP," "immediately," or "press" at the end of a sentence.	Self-explanatory.	urgency	4
11	"now" at the end of a sentence.	Self-explanatory.	urgency	3
12	Capitalized NO.	Example: "NO impact"	urgency	3
13	"hot" somewhere in the message.	Example: "Going hot with target A"	urgency	2

3.2 Statistical analysis: maximum entropy

Maximum entropy (MaxEnt) is a statistical modeling technique in which a dataset from a seemingly random process is used to make predictions about future data output. For this project, the OpenNLP group's Maximum Entropy package[11], open source code written in Java, was given a subset of our data for which each message was tagged with a label of our conclusion of connotative content as a training set. Training data was derived from chat examples other than the testing dataset, from the same data source and event. Approximately twenty samples representing each of uncertainty, urgency, and "other" were used for training. The program used this training data to develop a set of features containing information about chat statements that contain, according to our training data, urgency, uncertainty, and neither (other). When the trained system was then applied to the test data, it automatically classified chat statements as containing cues of urgency, of uncertainty, or other.

3.3 Combined rule-based and statistical analysis

In an attempt to make the best use of each of the methodologies, we applied a combination of our rule-based analysis and the maximum entropy statistical analysis. Software code was written to combine MaxEnt and our cues for a parallel analysis. For each message within each of three datasets, the decisions of MaxEnt and our cue table are considered together and final results are produced as shown in Table 2. Cue table confidence scores were divided by five to force a basis for comparison with MaxEnt confidence scores. If the decisions of MaxEnt and the cue table are the same, then the final decision of the combined algorithm is that same decision. If MaxEnt indicates urgency and the cue table indicates uncertainty, then the final decision will be determined by the highest confidence score between them. Finally, if MaxEnt indicates urgency or uncertainty and the cue table indicates other, the final decision is based on the MaxEnt confidence score. If the MaxEnt confidence score is greater than .6, then the final decision will match the MaxEnt decision for that message, otherwise the final decision is other.

Table 2: Parallel analysis with MaxEnt and cue table

		Cue Table		
		Urgency	Uncertainty	Other
MaxEnt	Urgency	Urgency	Highest Confidence Scorer	If MaxEnt Confidence Score > .6, Urgency; Otherwise, Other
	Uncertainty	Highest Confidence Scorer	Uncertainty	If MaxEnt Confidence Score > .6, Uncertainty; Otherwise, Other
	Other	Highest Confidence Scorer	Highest Confidence Scorer	Other

4. RESULTS

4.1 Information extraction metrics

Recall and precision are commonly used performance measures for tasks similar to this project. The meanings of recall and precision can be clarified by the Venn diagram of Figure 1 in which the circle on the left represents all of the information of interest in the dataset (that is, the ground truth) and the circle on the right represents the information selected by the software analysis. The rectangle represents the entire dataset (the Universe).

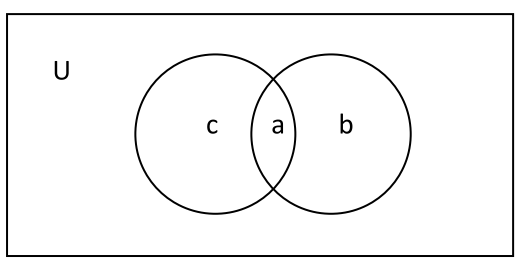

Figure 1: Venn Diagram. The rectangle, labeled U, represents all of the data (that is, the Universe). The circle on the left (a + c) represents all of the information of interest. The circle on the right (a + b) represents the information selected by an automatic analysis. Therefore, the intersection a represents the information of interest that was correctly identified by automatic analysis.

A recall measure represents the amount of correct, relevant information that was identified in comparison to the total amount of relevant information (that is, the ground truth) within the dataset. A recall score of 1.0 would mean that all of

the relevant information was correctly identified. It is a measure of the completeness of the data identified. The equation for recall, as represented by the diagram of Figure 1, is:

$$\text{Recall} = \frac{a}{a+c} \tag{1}$$

A precision measure represents the amount of information that was correctly identified in comparison to the amount of all of the information that was identified by the analysis. The equation for precision is shown, below. A perfect precision score of 1.0 means that all of the information selected as being relevant is actually relevant. Note that this wouldn't necessarily mean that all of the relevant information in the dataset has been detected.

$$\text{Precision} = \frac{a}{a+b} \tag{2}$$

The F-measure is the weighted harmonic mean of precision and recall, useful for comparing capabilities of systems as a single measure. For some analysis applications, one of either recall or precision may be more highly valued and that would determine the weight of each of them in the calculation of the F-measure. The research metric traditionally used is the balanced F-score, with evenly weighted recall and precision:

$$\text{F} = \frac{2\ x\ (precision\ x\ recall)}{precision + recall} \tag{3}$$

4.2 Analysis of Results

Our attempts to recognize urgency were unsuccessful. The cues we thought we observed were vague to begin with and focused on keyword matching. After-test review of the data showed that some overgeneration was caused by rule 12 of Table 1 that looked for a capitalized "NO" as an indication of urgency, but the rule matched numerous references to a chat participant whose function name included the word NO within it. Improving the recognition of urgency would require a completely new look at the problem. Urgency might be better recognized if the time between chat entries and a count of misspelled words were used as cues.

The results for recognizing uncertainty using the cue table alone were also disappointing, but the results of using the parallel algorithm, as well as the further scores achieved for the cue table by manipulation of data rules were encouraging and point towards some validation of the project's direction; the scores achieved in this project were comparable to scores achieved in very early analyses such as the third Message Understanding Conference of 1991. Table 3 shows the values for precision, recall and the balanced F-score for analysis of the dataset for each of the analysis methodologies - rule-based cue analysis, maximum entropy, and parallel analysis for uncertainty. Precision, recall, and F-scores are multiplied by 100, as had been the practice of the DARPA funded Message Understanding Conference (MUC) evaluations.

The cue table recall score was 40.48 and the precision score was 46.58. Manual review of the labeling indicated that a large amount of the overgeneration by the cue table rule-based algorithm was due to one particular rule – the ellipsis rule (rule #9 in Table 1). The rule labeled every chat entry containing ellipsis to be representative of uncertainty. Rule #8, marking an entry as uncertain if it contains a question *and* an ellipsis, was correct a larger percentage of the time. Eliminating rule #9 increased the precision significantly (to 75.00; as shown by parenthesized entry in Table 3). However, eliminating that rule reduced the recall value because some of the recognitions would have been valid, but the reduction in recall was less significant than the increase in precision, as shown by the increase in the F-score. It may be that further investigation could refine a rule or ruleset for recognizing uncertainty in chat messages containing ellipsis.

As mentioned before, rule #7, labeling messages containing the phrase "Which <noun>?" as demonstrating uncertainty, was the only rule developed that would require parsing or part-of-speech tagging. With further investigation, or within

other chat databases, deeper grammatical analysis might produce more and/or stronger cues of uncertainty. It was also noted during this project that phrasing of messages contributed to manual detection of uncertainty. For example, the question “Do you know if we should track this target?” conveys more uncertainty than the question “Where is target A?” Although both are requests for information, the tone of the first question is tentative, whereas the tone of the second question is more business-like. However, this cue of uncertainty was not considered during algorithm development due to lack of time. This would be something to consider in future work.

As can be noted from Table 3, maximum entropy analysis recall of uncertainty is significantly higher than that of cue analysis – it was able to recognize many more of the chat entries presenting uncertainty. Its precision, however, was lower than that of cue analysis. Statistical analyses, like MaxEnt, often can be improved (to a point) with additional training. It would be interesting to determine the amount of training data that would provide the best performance. It should be noted that MaxEnt, as we applied it, is not able to detect connotative meanings where the cues are present across messages. We used MaxEnt as a “bag of words” approach to message classification, meaning that MaxEnt did not take the order of the words within each message into account; further investigation might look into what word order and relationships can bring to recognizing connotative meaning.

Combining the rule-based algorithm and MaxEnt into a parallel algorithm was implemented upon realizing that MaxEnt recall scores were much better than cue analysis, and cue analysis precision scores were a bit better than MaxEnt. This parallel algorithm resulted in an improvement in overall performance; the precision scores are higher than both the cue table and MaxEnt alone, however the recall scores are lower than MaxEnt, but higher than the cue table. The reduction in recall (with respect to MaxEnt) is not as significant as the increase in precision (with respect to the cue table and MaxEnt), as indicated by the increase in F-score (with respect to both methodologies). It would be interesting to try different threshold values for MaxEnt in the parallel algorithm to see how the performance of the parallel algorithm is affected and find the optimal threshold value.

Table 3: Uncertainty
(Parenthesized entries are results of cue analysis without Rule #9.)

Cue Table			MaxEnt			Parallel		
Recall x 100	Precision x 100	F-score x 100	Recall x 100	Precision x 100	F-score x 100	Recall x 100	Precision x 100	F-score x 100
40.48 (32.14)	46.58 (75.00)	43.32 (45.00)	72.72	39.35	51.07	55.95	62.67	59.12

5. SUMMARY

Chat, as a more expressive medium than formal text, contains technical content, as well as cues expressing emotions the users may be feeling. In order to exploit both of these facets of chat, techniques must be developed to go beyond understanding only the technical content and recognize any connotations chat messages may express. This paper has shown how encouraging results were achieved when a combination of rule-based and statistical techniques was used to recognize uncertainty in military chat messages. As the use of chat increases in the military domain, further research in this area, as well as others, is necessary to enable more useful automatic intelligence exploitation of chat messages.

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